Civil, Construction and Environmental Engineering Conference Presentations and Proceedings
Civil, Construction and Environmental Engineering

2007

Hot Mix Asphalt Dynamic Modulus Prediction Models Using Neural Networks Approach

Halil Ceylan
Iowa State University, hceylan@iastate.edu

Sunghwan Kim
Iowa State University, sunghwan@iastate.edu

Kasthurirangan Gopalakrishnan
Iowa State University, rangan@iastate.edu

Reference to this paper should be made as follows: Ceylan, H., Kim, S., and Gopalakrishnan, K. "Hot Mix Asphalt Dynamic Modulus Prediction Models Using Neural Networks Approach," ANNIE 2007, ANNs in Engineering Conference, St. Louis, Missouri, November 10-14, 2007.

HOT MIX ASPHALT DYNAMIC MODULUS PREDICTION MODELS USING NEURAL NETWORKS APPROACH

HALIL CEYLAN
Assistant Prof., Iowa State University, Ames, IA

KASTHURIRANGAN GOPALAKRISHNAN
Research Scientist, Iowa State University, Ames, IA

SUNGHWAN KIM
Postdoctoral Res. Assoc., Iowa State University, Ames, IA

ABSTRACT
The primary objective of this study is to develop a simplified Hot Mix Asphalt (HMA) dynamic modulus (|E*|) prediction model with fewer input variables compared to the existing regression based models without compromising prediction accuracy. ANN-based prediction models were developed using the latest comprehensive |E*| database that is available to the researchers containing 7,400 data points from 346 HMA mixtures. The ANN model predictions were compared with the existing regression-based prediction models which are included in the latest Mechanistic-Empirical Pavement Design Guide (MEPDG). The ANN based |E*| models show significantly higher prediction accuracy compared to the existing regression models although they require relatively fewer inputs. The findings of this study present a "paradigm shift" in the way the hot-mix asphalt material characterization has been handled by pavement materials engineers.

INTRODUCTION

The dynamic modulus (|E*|) is one of the Hot Mix Asphalt (HMA) stiffness measures that determines the strains and displacements in flexible pavement structure as it is loaded or unloaded. Many studies have been conducted over the last 50 years related to the development of HMA dynamic modulus (|E*|) test procedures and prediction models. Among these, the |E*| modulus test (also referred to as the Simple Performance Test) recommended by National Cooperative Highway Research Program (NCHRP) 9-19 study (Witczak et. al., 2002) and the |E*| prediction equation developed by Witczak and his colleagues in 1999 (Andrei et. al., 1999) has been incorporated into the new mechanistic empirical pavement design guide (MEPDG) (NCHRP, 2004). The input variables for the 1999 version |E*| model include aggregate gradation, mixture volumetrics, viscosity of the asphalt binder (η), and loading frequency (f). The aggregate gradation variables include percent passing #200 sieve ($\rho_{\#200}$), percent retained #4 sieve ($\rho_{\#4}$), percent retained 9.5 mm sieve ($\rho_{9.5mm}$), and percent retained 19 mm sieve (ρ_{19mm}). The mixture volumetrics includes air void (V_a) and effective binder content (V_{beff}).

A new revised version of the Witczak's |E*| predictive model has been developed to improve the characterization of asphalt mixtures in dynamic mode of loading (Bari and Witczak, 2006, Azari et. al., 2007). Furthermore, the new |E*| prediction model adopting the asphalt binder shear modulus ($|G_b*|$) and phase angle (δ) as variables instead of η and f would directly link to the Superpave Binder Performance Grading (PG) system and the associated binder testing (Bari and Witczak, 2006). In additional, the new |E*| model is based on a more comprehensive |E*| database containing 7,400 data points from 346 HMA mixtures covering a variety of binder stiffness as a result of testing lab-aged, plant mix, and field-aged cores. The new Witczak |E*| model was incorporated in a recent version of MEPDG (version 1.0) with the 1999 version |E*| model. Even though the new revised model predicts |E*| with higher accuracy compared to the 1999 model, the nonlinear regression technique was still employed in the model development so that there is still a significant scatter especially at the lower and higher |E*| modulus values (Bari and Witczak, 2006; Azari et. al., 2007). By accurately characterizing the HMA dynamic modulus, it will be possible to predict the flexible pavement performance (rutting and cracking) will greater confidence.

Recently, researchers at Iowa State University (ISU) have developed a novel approach for predicting HMA dynamic modulus using the Artificial Neural Network (ANN) methodology. The comprehensive |E*| database containing 7,400 data records, which were used in the development of revised |E*| model (Bari and Witczak, 2006), were also used in developing the ANN models. This paper describes the ground-breaking work on the development of ANN-based |E*| prediction models, the comparison of ANN model predictions with the Witczak model predictions, and the feasibility of input variables optimization to ANN model predictions.

ANN DATABASE PREPARATION

Input variables for the |E*| ANN prediction model were retrieved from the NCHRP Report 567 CD-ROM (*CRP-CD-46*) "Simple Performance Tests: Summary of Recommended Methods and Database." (Witczak, 2005). The *CRP-CD-46* included as an appendix in the NCHRP report 567 contains not only |E*| new database but also all data and information colleted and used during NCHRP 9-19 study. The eight input variables of the 1999 and 2006 version |E*| predictive equations were used in the two different types of ANN models (ANN 1999 and ANN 2006), respectively. The one output variable was the |E*| in both the ANN models. A total of 7,400 data records (which was also used in developing the new and revised |E*| model) was used in developing the ANN models.

The data were divided randomly into two different subsets: the training data subset containing 6,900 data points and the testing data subset which consisted of 500 data points. Both datasets were normalized within the range of -2 to 2 for input values and the range of 0.1 to 0.9 for output values to satisfy the transfer function (sigmoid) range and to prevent network saturation, which could impede the network's performance. The training data subset was used to train the backpropagation ANN |E*| prediction model and the testing data subset were used to examine the statistical accuracy of the developed ANN model. Backpropagation ANNs are very powerful and versatile networks that can be taught a mapping from one data space to another using a representative set of patterns/examples to be learned. The term "backpropagation network" actually refers to a multi-layered, feed-forward neural network trained using an error backpropagation algorithm. The learning process performed by this algorithm is called "backpropagation learning" which is mainly an "error minimization technique" (Haykin, 1999).

ANN |E*| PREDICTION MODEL DEVELOPMENT

A typical four-layered, i.e., one input- two hidden–one output layer, feed forward error-back propagation ANN architecture, as shown in Fig. 1, was used in this study. To ensure efficient convergence and the desired performance of the trained network, several parameters were incorporated in the training phase. These parameters included the training rate, the momentum term, and the number of learning cycles (epochs).

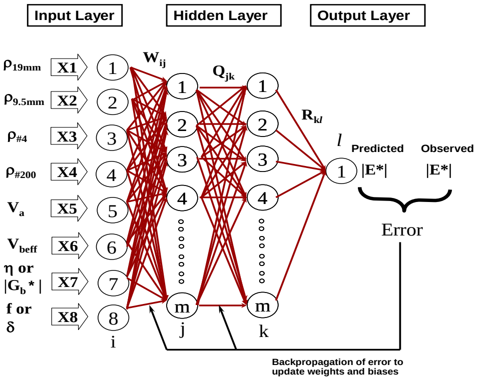

Figure 1. Four-layered neural network architecture

The training rate is a factor that proportions the amount of adjustment applied each time the weight is updated. A small training rate might result in slower convergence and dropping into the local minima conditions in the weight-error space. A large training rate often causes the convergence behavior of the network to oscillate and possibly never converge (Owusu-Aabio, 1998). The use of a momentum term could carry the weight change process through one or more local minima and get it into global minima. The training rate and the momentum coefficient used in the study were 0.4 and 0.6, respectively.

ANN 1999 |E*| prediction model has eight input parameters including the four aggregate gradation variables (ρ_{19mm}, $\rho_{9.5mm}$, $\rho_{\#4}$, $\rho_{\#200}$), two mixture volumetric variables (V_{beff}, V_a), one asphalt binder rheology property variable (η) and one loading frequency property (f). ANN 2006 model also has eight input parameters corresponding to the input variables of 2006 version Witczak |E*| prediction model, which adopted $|G_b{}^*|$ and δ as variables instead of η and f. Both ANN models have |E*| as one output neuron. Several network architectures with two hidden layers were examined to determine the optimum number of hidden layer nodes through a parametric study. Overall, the training and testing mean squared errors (MSEs) decreased as the networks grew in size with increasing number of neurons in the hidden layers. The error levels for both the training and testing sets matched closely when the number of hidden nodes approached 30 as in the case of 8-30-30-1 architecture (8 input, 30 and 30 hidden, and 1 output neurons, respectively). Figure 2 shows the training and testing MSE progress curves for the 8-30-30-1 network for 10,000 learning cycles or training epochs. The 8-30-30-1 architecture was chosen as the best architecture for both the ANN 1999 and 2006 model based on its lowest training and testing MSEs in the order of 2×10^{-4}. Both the training and testing curves for the output are in the same order of magnitude thus depicting proper training. The almost constant MSEs obtained for the last 8,000 epochs (see Fig. 2) also provided a good indication of adequate training for this network.

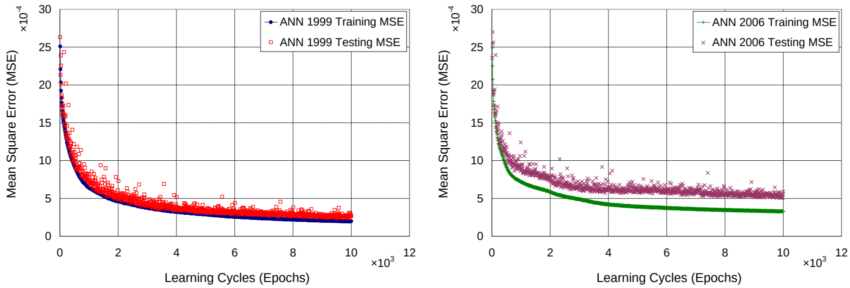

Figure 2. Training and testing progresses of the ANN models

ANN |E*| PREDICTION MODEL RESULTS

The *goodness-of-fit* statistics for the ANN model predictions in arithmetic scale were performed using statistical parameters such as the correlation coefficient (R^2), the standard error of predicted values divided by the standard deviation of measured values (S_e/S_y) and the absolute average error (AAE). The R^2 is a measure of correlation between the predicted and the measured values and therefore, determines accuracy of the fitting model (higher R^2 equates to higher accuracy). The S_e/S_y and the AAE indicates the relative improvement in accuracy and thus a smaller value is indicative of better accuracy. A set of criteria originally developed by Pellinen (2001) were also adopted in this evaluation.

The results of statistical analysis are presented in Fig. 3 for the 500 testing data points. As mentioned previously, the 500 test vectors form an independent dataset which was not used in training the ANN and it was used to test the accuracy of the trained ANN. Clearly, the ANN 1999 and 2006 model predictions show “excellent” statistics compared to Witczak model predictions. Especially, the AAE obtained using ANN is almost half that of Witczak’s model. It is also noticed that the 1999 and the 2006 Witczak predictions are more scattered below and above the line of equality (45 degree line) with increasing |E*| values. Especially, the 1999 Witczak |E*| model seems to under-predict the actual measurement while the 2006 Witczak |E*| model tends to over–predict the actual measurements. In terms of performance, this prediction inaccuracy may translate into the risk of premature failure of the asphalt layer in rutting or fatigue. However, ANN model predictions are closely around the line of equality without bias and therefore there is a higher chance of preventing premature distress failure. It is also interesting to note that the ANN 1999 models show slightly better goodness of fit statistics than the ANN 2006 models.

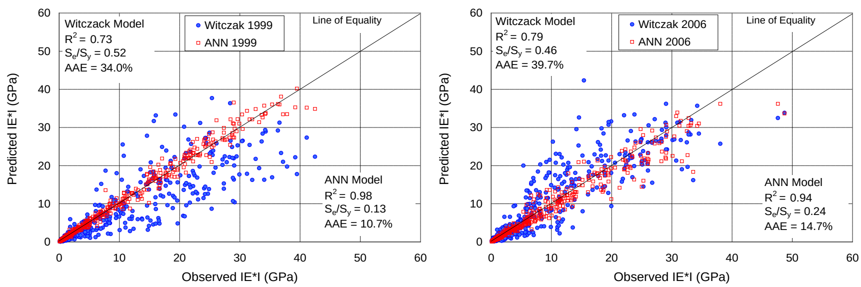

Figure 3. Predicted versus observed |E*| in Witczak and ANN models

OPTIMIZATION OF INPUT VARIABLES FOR ANN MODEL

Witczak equations include eight input variables. However, sometime, it is hard to obtain all of these variable values in actual situation. Preliminary investigations were carried out to obtain the optimum number of input variables for the ANN models compared to Witczak models without compromising prediction accuracy. The asphalt binder rheology properties (η, $|G_b^*|$, δ) were selected as the essential input variables and the effect of including/excluding other variables on ANN model predictions were examined. Among the developed ANN models, the ANN 1996-6 and ANN 2006-6 models using six input varaibles (ρ_{19mm}, $\rho_{\#4}$, V_a, V_{beff}, η or $|G_b^*|$, f or δ) and the ANN 1999-4 and ANN 2006-4 models using four input varaibles ($\rho_{\#4}$, V_{beff}, η or $|G_b^*|$, f or δ) are presented in Figs. 4 and 5 for illustaration.

Even though the numeber of input varaibles were reduced in the development of models, ANN models shown in Figs. 4 and 5 still show better performance of |E*| predictions compared to Witczak models. Especially, the goodness-of-fit statistics for the ANN 1999-6 and the ANN 2006-6 models are very similar to the results obtained with the eight input varaibles.

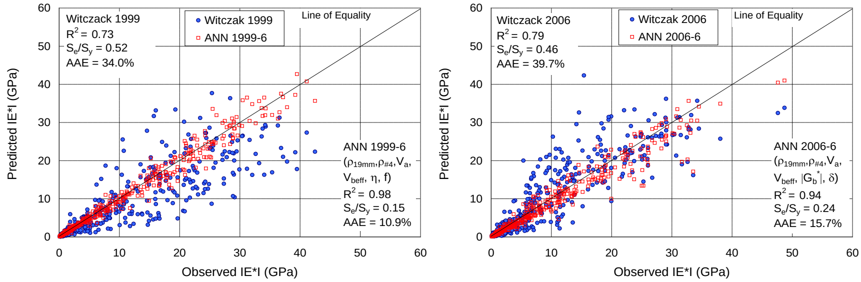

Figure 4. Comparison between Witczak and ANN-6 models

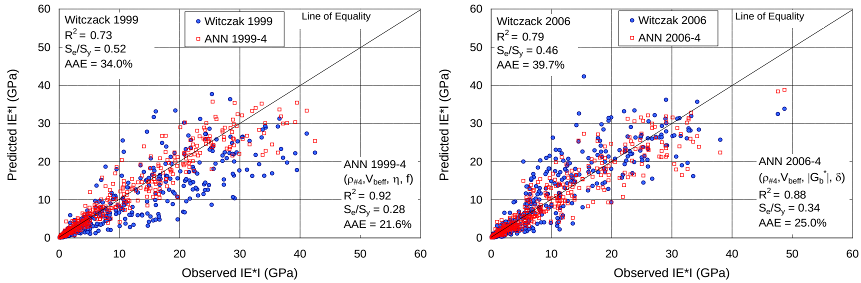

Figure 5. Comparison between Witczak and ANN-4 models

SUMMARY AND CONCLUSIONS

The primary objective of this study is to develop a simplified Hot Mix Asphalt (HMA) dynamic modulus (|E*|) prediction model with fewer input variables compared to the existing regression based models without compromising prediction accuracy. ANN-based prediction models were developed using the latest comprehensive |E*| database that is available to the researchers containing 7,400 data points from 346 HMA mixtures. It was found that by using less than eight input variables, ANN models still showed significantly better performance to Witczak models for |E*| prediction. Especially, the ANN models using six input variables ($\rho_{\#4}$, V_a, V_{beff}, ηor $|G_b^*|$, f or δ) were very similar to the results obtained with the eight input variables.

The results of this study have significant implications in the context of advancing the state of the art in mechanistic-empirical pavement analysis and design. ANN models trained over comprehensive datasets could be successfully incorporated into MEPDG as surrogates for pavement materials characterization models and pavement performance prediction models. Because ANNs excel at mapping in higher-order spaces, such models can go beyond the existing univariate relationships between pavement structural responses and performance (such as the subgrade strain criteria for rutting). ANNs could be used to examine several variables at once and the interrelationships between them. ANNs could also be used to develop models for distress phenomena such as thermal cracking, block cracking, and rutting in HMA pavements, and faulting and D-cracking in concrete pavements. With the use of the computational intelligence tools, the findings of this study present a "paradigm shift" in the way the HMA material characterization has been handled by pavement materials engineers.

REFERENCES

Andrei, D., Witczak, M. W., and Mirza, M. W., 1999, "Development of a Revised Predictive Model for the Dynamic (Complex) Modulus of Asphalt Mixtures," National Cooperative Highway Research Program 1-37 A Inter Team Report, University of Maryland.

Azari, H., Al-Khateeb, G., Shenoy, A., and Gibson, N., 2007, "Comparison of Measured STP E* of ALF Mixtures with Predicted E* Using NCHRP 1-37 A and Witczak's new equations," CD-ROM, Presented at 86th Annual Transportation Research Board Meeting, Transportation Research Board, Washington, D.C.

Bari, J. and Witczak, M. W., 2006, "Development of a New Revised Version of the Witczak E* Predictive Model for Hot Mix Asphalt Mixtures," Journal of the Association of Asphalt Paving Technologists, Vol. 75.

Haykin, S., 1999, "Neural Networks: A Comprehensive Foundation," Prentice-Hall, Inc., NJ.

National Cooperative Highway Research Program (NCHRP), 2004, "Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures," Available one line at: http://trb.org/mepdg, National Cooperative Highway Research Program 1-37 A, Transportation Research Board, Washington, D.C.

Owusu-Aabio, S., 1998, "Effect of Neural Network Topology on Flexible Pavement Cracking Prediction," Computer Aided Civil Infrastructure Engineering 13, pp. 349–355.

Pellinen, T. K., 2001, "Investigation of the Use of Dynamic Modulus as an Indicator of Hot–Mix Asphalt Performance," Ph.D. Dissertation, Arizona State University.

Witczak, M. W., Kaloush, K., Pellinen, T., El-Basyouny, M., and Quintus, H. V., 2002, "Simple Performance Test for Superpave Mix Design," National Cooperative Highway Research Program Report 465, Transportation Research Board, Washington, D.C.

Witczak, M. W., 2005, "Simple performance tests: Summary of Recommended Methods and Database," National Cooperative Highway Research Program Report 547, Transportation Research Board, Washington, D.C.